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INTELLIGENT COMPUTER BASED RELIABILITY ASSESSMENT OF MULTICHIP MODULES

University of Massachusetts

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13. ABSTRACT (Maximum 200 words)
A novel methodology for design assessment of MCM packages is presented using finite element analysis and a Taguchi based design of experiments technique. This methodology enables the design engineer to rapidly estimate the quality of candidate designs and thereby select better designs. The proposed method allows the designer to generate a robust finite element model of the physical process which is also numerically efficient, to identify the design parameters that are critically important to the performance of the design and also to investigate the effect of tolerances on the significant design parameters. A detailed description is presented along with a MCM design example to illustrate the proposed method.

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1 Introduction

To deliver reliable Multichip Modules (MCMs) in the face of rapidly changing technology, computer-based tools are needed for predicting the thermal mechanical behavior of various MCM package designs and selecting the most promising design in terms of performance, robustness and reliability. The design tool must be able to address new design technologies, manufacturing processes, novel materials, application criteria, and thermal environmental conditions. Furthermore, the tool must be able to assess the thermal-mechanical and electrical performance of various alternative device configurations as quickly as possible and select the optimum design configuration as early as possible in the design process. This is extremely important because studies have shown that, while the bulk of a product's life cycle cost may be incurred in its later stages, these costs are actually *committed* early in the design process. Reliability is one of the most important factors for determining design quality and hence must be a central condition in the design of Multichip Module packages. Reliability must be designed *a priori* into the device since it cannot be added *a posteriori* after product development.

In an ideal design environment engineers would draw upon extensive empirical databases of from previous design efforts to help determine which device configurations offer superior electrical, thermal and mechanical performance characteristics. Unfortunately, in the real world of multichip modules such databases seldom exist. Another approach to the reliability assessment of devices is the use of deterministic failure prediction methods. Most of these methods require the use of numerical tools for predicting the mechanical behavior of the device since accurate closed form analytical solutions are almost impossible to obtain. The shortcomings of some of the existing failure prediction methods is discussed in Section 2.

Clearly, design engineers need computer based simulation tools for rapid and efficient electrical, thermal and mechanical modeling and optimization of advanced devices. For three dimensional thermal and mechanical simulation of advanced devices, the finite element method (FEM) is increasingly becoming the numerical method of choice. FEM is a versatile and sophisticated numerical technique for solving the partial differential equations that describe the physical behavior of complex designs. For this purpose the design must be geometrically represented and discretized into a number of subdivisions, known as elements and connected by points called as nodes. This process is known as meshing, resulting with a finite element mesh. Based on the analysis results and the accuracy required by the user, the mesh may need to be further refined by increasing the number of nodes (i.e., the degrees of freedom) in the mesh. Thus, the development of a sufficiently accurate and valid finite element model of a physical system is an iterative and often time consuming process.

The inherent expertise, complexity and time involved in finite element modeling and analysis has been currently limited in its application as a tool for early design evaluation. Yet, it is possible to overcome these drawbacks and offer engineers a finite element based design tool for rapid design evaluation by simply applying proven artificial intelligence technology, feature based modeling and object oriented techniques to streamline and automate finite element modeling and analysis as much as possible. Finally, by adopting into the design process the concepts espoused by Taguchi and others for high quality manufacturing, a high quality design methodology for multichip module packages can be realized. In this manner the design space for advanced package design can be efficiently explored early in the design process and the most promising package configuration in terms of performance and robustness can be selected for prototyping and testing.

Ideally, a design engineer would want all the features described above integrated and implemented as a single multichip module package design tool. Most of the tools available today usually employ either finite element techniques [1] or finite differences and analytical techniques [2] for MCM design, analysis, and reliability assessment. AUTOTHERM™ is a MCM design tool developed by Mentor Graphics for Motorola Inc. [1]. This tool performs thermal analysis of MCM packages using finite element analysis techniques. The tool uses the philosophy of object oriented representation of components and simplified specification of boundary conditions for the thermal analysis so that the user need not be an expert in using finite element techniques. The MCM design package CADMP [2] is a PC based design tool that allows thermal analysis and consequent reliability assessment of IC, hybrid and MCM packages. Different package types that can be assessed are dual-inline package (DIP), quad flatback (QFP), pin-grid array (PGA), single in-line package (SIP) and land grid array (LGA). Finite difference techniques are used for performing the thermal analysis. It also has the capability to include various components such as substrate, substrate attach, leads, lead seal and interconnects. Environmental conditions can also be modeled. Finally, it includes a detailed reliability analysis module which allows the user to choose a desired failure mechanism (model). Reliability analysis is performed based on the thermal solution.

All of the current tools perform thermal and or stress analysis and do not address the issues of robustness and optimality of MCM designs. Moreover, the reliability prediction techniques (cycles to failure, N_f) are based on closed form analytical models and often fail by order of magnitude in predicting N_f. They can, at best, be used to compare different designs. This philosophy is adopted in the current research. Candidate MCM designs are evaluated in terms of

the reliability performance parameters (maximum temperature/stress/strain) rather than the absolute reliability of the device. In this regard we propose a methodology and associated computer based design tool for multichip modules which embodies these ideas and addresses the issues of optimum and robust MCM package designs, an issue that has not been addressed by any of the tools discussed above. An object oriented approach and design of experiments methodology is adopted and integrated into the already existing Intelligent Multichip Module Analyzer (IMCMA) system. The different features of IMCMA are briefly outlined in Section 4. The reader is referred to [3] and [4] for additional details.

2 Problems with existing MCM design quality assessment

MCM design configurations are usually evaluated based on the reliability (cycles to failure) of the device. Previous research has shown that the various modes of failure in such packages can be broadly classified into structural or mechanical and non structural or electrical modes of failure [5] [6]. Based on data it can be inferred that the electrical modes of failure comprise about 10% of total component failures, thus indicating that the mechanical modes of failure are more critical [7].

To predict the reliability of MCMs, the failure mechanisms need to be identified and modeled accurately. This is done using failure prediction modeling techniques. Figure 1 schematically outlines the existing methods of failure prediction techniques. The various failure prediction modeling techniques can be broadly classified into two methods: empirical failure prediction methods (EFPMs) and deterministic methods. EFPM models are based on field data on systems and accelerated tests of various components. EFPM models can take advantage of extensive test and field data and accommodate irregular (actual) loading patterns. This data is used to compute a mean time between failures (MTBF). Depending on the quality of data MTBF results may vary

dramatically. The problems with application of these methods to MCM reliability assessment is the lack of experimental data.

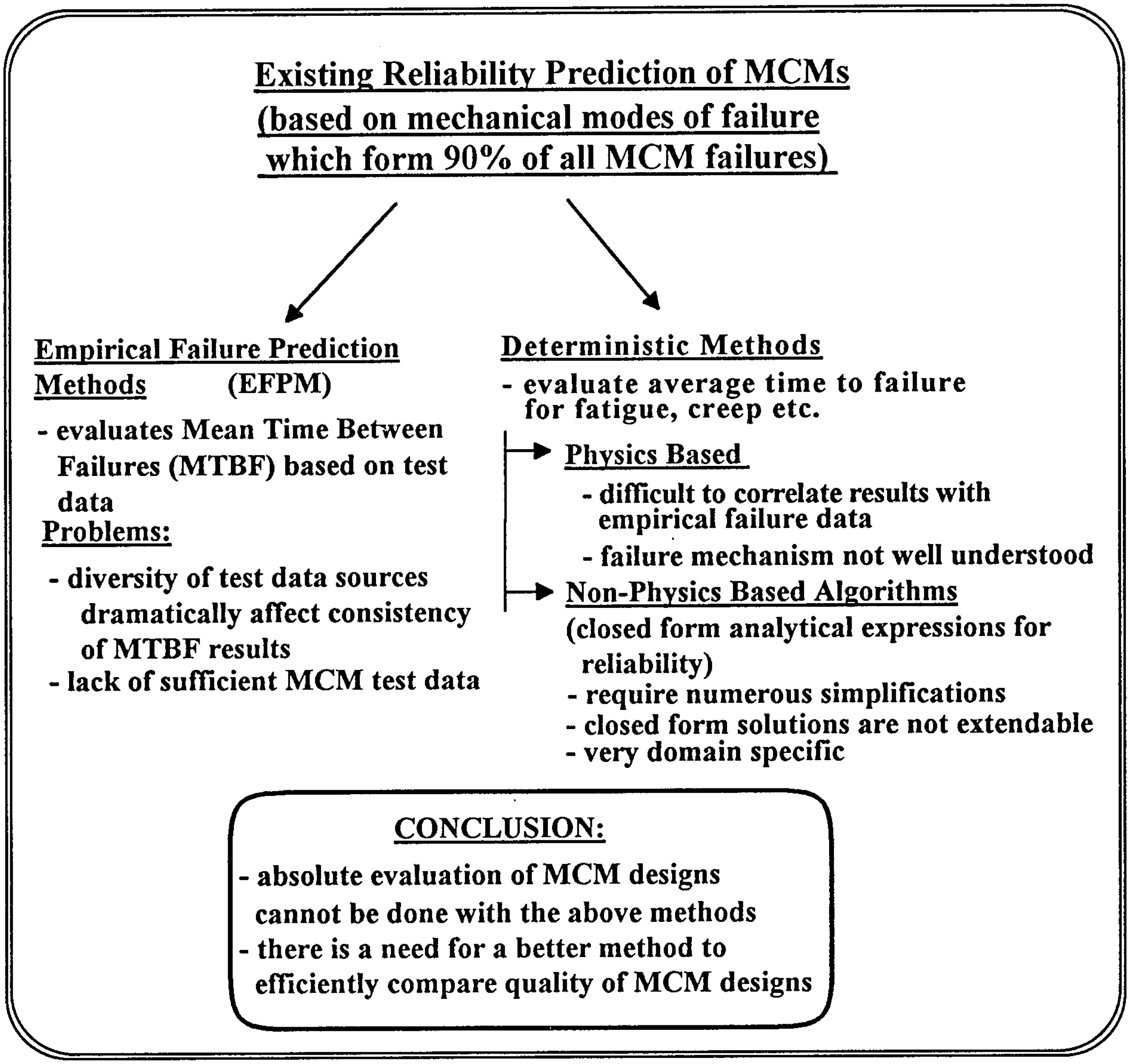

Figure 1: Existing methods of reliability prediction of MCM package designs

Deterministic methods use physics of failure concepts to determine an average and in some cases, a minimum time to failure for fracture, fatigue, creep rupture corrosion and general mechanical wear. These methods require inputs of certain quantities like maximum stress/strain/temperature for the component whose reliability has to be predicted based on certain

loading conditions. These quantities, usually estimated using finite element methods, are often difficult to correlate with empirical failure data due to the following reasons.

► The mechanisms of failure are still not well understood.

► The prediction techniques based on physics of failure models are highly inaccurate.

► The material properties of the materials used in MCMs cannot be accurately determined

Other failure prediction methods are non-physics based which present closed form analytical expressions for reliability. Such closed form solutions can only be arrived at after making numerous simplifying assumptions regarding the thermal and mechanical behavior of the device. The validity of these assumptions must be verified by fabrication and device testing. Moreover, the closed form solutions cannot be extended beyond the very narrow scope for which they have been derived. For these reasons nonphysics based reliability prediction methods are not suitable for early design optimization of MCM packages. The following section outlines the proposed methodology for evaluation and optimization of candidate MCM package designs.

3 Proposed MCM design quality assessment

To get an *a priori* estimate of the quality of a design, a new methodology needs to be adopted. We propose to incorporate design of experiments (DOE) techniques into our design process. Any of the standard DOE techniques currently in use could have been selected. However, the Taguchi method has been adopted primarily due to it's ease of implementation. The assumptions inherent to DOE (sometimes restrictive) are not a burden to this proposed methodology [8], [9] and [10].

For design optimization, candidate MCM designs are compared and evaluations are made relative to each other. The approach taken in the present research for assessing design quality is to

infer the design quality directly from the mechanical *performance parameters* (**PPs**) such as the maximum temperature, stress and total strain range (TSR). It is well known that these parameters directly affect the reliability of the device. For example, a design with a lower performance parameter value is presumed to be having a higher intrinsic design quality when compared to a design which has a higher performance parameter value. Note that in this approach the absolute reliability of a device, such as the number of cycles to failure is not sought. Instead, it can be argued that early design decisions are made in a relative context, and therefore design engineers are more interested in the relative performances of various design configurations.

Performance parameters discussed above are obtained based on certain loading and boundary conditions after performing a finite element analysis. Because the finite element method provides a numerical solution of the governing differential equations and boundary conditions, it does not have robustness problems associated with non-physics based reliability prediction methods. ***If properly applied***, it does not suffer from accuracy and applicability problems associated with closed form analytical solutions.

Before presenting the proposed methodology, the concepts of optimality and robustness in the context of modeling and design applicable to the domain of MCM packages are discussed in the following section.

3.1 Optimality and robustness

During the stages of physical idealization and the finite element modeling and analysis process, various modeling simplifications are made to enable rapid finite element analysis. As with all modeling processes, these modeling simplifications invariably affect the accuracy of the solution obtained. Hence, they are to be selected judiciously by the designer. Modeling simplifications that

produce the least variation in the performance parameter imply that the finite element model is robust with respect to them.

Using the Taguchi DOE technique, we can investigate candidate designs based on one or more *performance parameters*. This method has been successfully used to improve the robustness of electronic circuits [11]. Using this method the designer can get useful information regarding how each of the design parameters affect the performance of the design. Various virtual experiments are run as outlined by the Taguchi design of experiments method which is a fractional factorial set of experiments. The results are then used to obtain an optimal design configuration based on the nature of the performance characteristic. For example, if the performance parameter is chosen as maximum temperature, then it is always desirable to chose the MCM design having the lowest maximum temperature as the optimal design from a mechanical behavior viewpoint.

By performing statistical calculations on the outcome of the experiments, one can obtain sensitivity information to identify design parameters that affect the performance parameter, and quantify them relative to each other. The Taguchi method uses a statistical technique called ANOVA (analysis of variance), which breaks the total variation in an observed experimental outcome into the relative *percent contributions* of factors which influence the experimental outcome. With the Taguchi method applied to experimental results we can obtain sensitivity information about the various design parameters as follows.

(a) *Near-optimum* design factors can be identified.

(b) Design parameters that contribute to the results can be identified and quantified.

(c) Predict the the *expected result* of the optimal design parameters.

For example, if there are 3 design variables (viz. A, B and C) discretized at two values, the equation for total variation may be written as :

$SS_T = SS_A + SS_B + SS_{AXB} + SS_C + SS_{AXC} + SS_{BXC} + SS_{AXBXC} + SS_E$

However, with reduced fractional factorial designs, the model becomes

$SS_T = SS_A + SS_B + SS_C + SS_E$

where, all interaction effects are confounded with the main effects of each design parameter. The term SS_A is called the sum-of-squares of design variable A and is defined as:

$$SS_A = \left[\Sigma\left(\frac{A_i^2}{n_{A_i}}\right)\right] - \frac{T^2}{N}$$

where

T = sum of all outcomes

A_i = sum of all outcomes of design parameter A at level i

n_{Ai} = number of outcomes of design parameter A at level i.

Similarly SS_B and SS_C are calculated. It should be emphasized that the MCM "virtual" experiment described above is completely deterministic, as opposed to any real world experiment. That is, for a given set of design parameters and corresponding finite element model, there is no variation in the outcome. In essence, in a finite element simulation there are no uncontrolled factors which influence the predictability of the outcome and thus, for our virtual experiment SS_e will be zero.

The percent contribution for each factor is not dependent on the error variance and for factor A, is computed using $P_A = SS_A/SS_T*100$. Similarly, P_B and P_C for design parameters B and C are computed. The portion of the total variation attributed to each design variable is reflected in the percent contribution. If the design variables and interaction levels were controlled precisely, then the total variation could be reduced by the amount indicated by the percent

contribution. The design variable with the highest percent value contributes most towards the variation observed in the experiment.

Other possible design variables for MCMs could be material properties associated with specific die attach materials, lead type, thicknesses of MCM layers, package lid, cavity depth, prescribed boundary conditions which may fluctuate, the number of chips in a cavity, etc. Virtually any continuous or discrete parameter (and even a selection of component type) can be a design variable in a Taguchi design of experiments methodology. This and the reduced number of experiments required to obtain near optimum designs are the main advantages of the Taguchi approach compared to more restrictive and computationally formal mathematical optimization techniques.

The fact that an optimal design may give an optimum performance level and NOT necessarily a performance consistency raises the issue of the robustness in the optimal design. The philosophy of a robust design is not to control the sources of variation affecting the design but make the design insensitive to their variability. The sources of variations affecting the performance of a design can arise from either manufacturing inconsistencies, environmental conditions or the variations in the design parameters themselves. The Taguchi method of design of experiments can also be used to obtain robust, near optimal designs by using two sets of orthogonal arrays, one called the inner array and the other called the outer array. The inner array is formed with the design parameters and the outer array is formed with other sources of variations, e.g., modeling simplifications, tolerances etc.

However, it is to be noted that the robust optimum design configuration obtained is not necessarily the global optimum. This is because with the Taguchi method the design space is

represented by discrete values of the design parameters which does not take into account the values the design parameters can have between or beyond these values. Nevertheless, this information can be used as a starting point in the search for an optimum design configuration for which other more mathematically rigorous optimization techniques could be used.

In the following section we propose a methodology that uses the Taguchi based DOE technique to obtain:

- a robust finite element model of a MCM package and
- a near optimal and tolerant MCM package design

It is assumed that the reader is familiar with the standard Taguchi DOE terminology that is being used in this report. If not, the reader is referred to any standard text on this subject ([8],[9])

3.2 Proposed methodology

The proposed methodology for MCM package design consists of three main steps:

► Parametric design

► Design space reduction

► Tolerance design

Figure 2 is an illustration of the proposed design methodology.

Parametric Design: This involves obtaining a robust finite element model and identifying a near optimal design based on the robust model. First, the designer identifies the complete design space which constitutes a set of design parameters that define the MCM design, the number of discrete levels and values at each level that are to be investigated. Similarly, the modeling simplification parameters along with number of levels and values at the levels are also identified. A performance parameter upon which the designs are rated and an allowable variance measure representing the maximum acceptable variance of the performance parameter due to different

values of modeling simplifications are then specified by the designer. The design parameters and their levels constitute a Taguchi *inner array*, while the modeling parameters and their levels are represented in a Taguchi *outer array*. These arrays are now "crossed" and the corresponding virtual experiments (finite element analysis simulations) are run to obtain the performance parameter value for each virtual experiment. Statistical analysis is then performed on the performance parameter values, and the variances in these values due to the modeling simplifications are determined.

If the computed variance of the performance parameter due to each modeling simplification is acceptable (below the specified acceptable variance), it implies that the modeling simplifications have no appreciable effect on the estimate of the performance of the design. Hence, any value can be selected for each of the modeling simplification parameters. Consequently, a judicious choice of modeling simplification parameter values, as is in our case, will be ones that will result in the most rapid finite element simulations (with least computational time). If any of the variances in the performance parameter due to certain modeling simplifications is above the acceptable variance specified, then it is suggested that the designer use the conservative values for the modeling simplification parameters to avoid large errors in the performance parameter values due to errors in finite element simulations. The performance parameter values corresponding to the modeling simplification parameter values chosen above are now used to generate an optimal combination of design parameter levels. A standard Taguchi statistical analysis is then used to compute the percent contribution of modeling simplification parameters to the performance parameter.

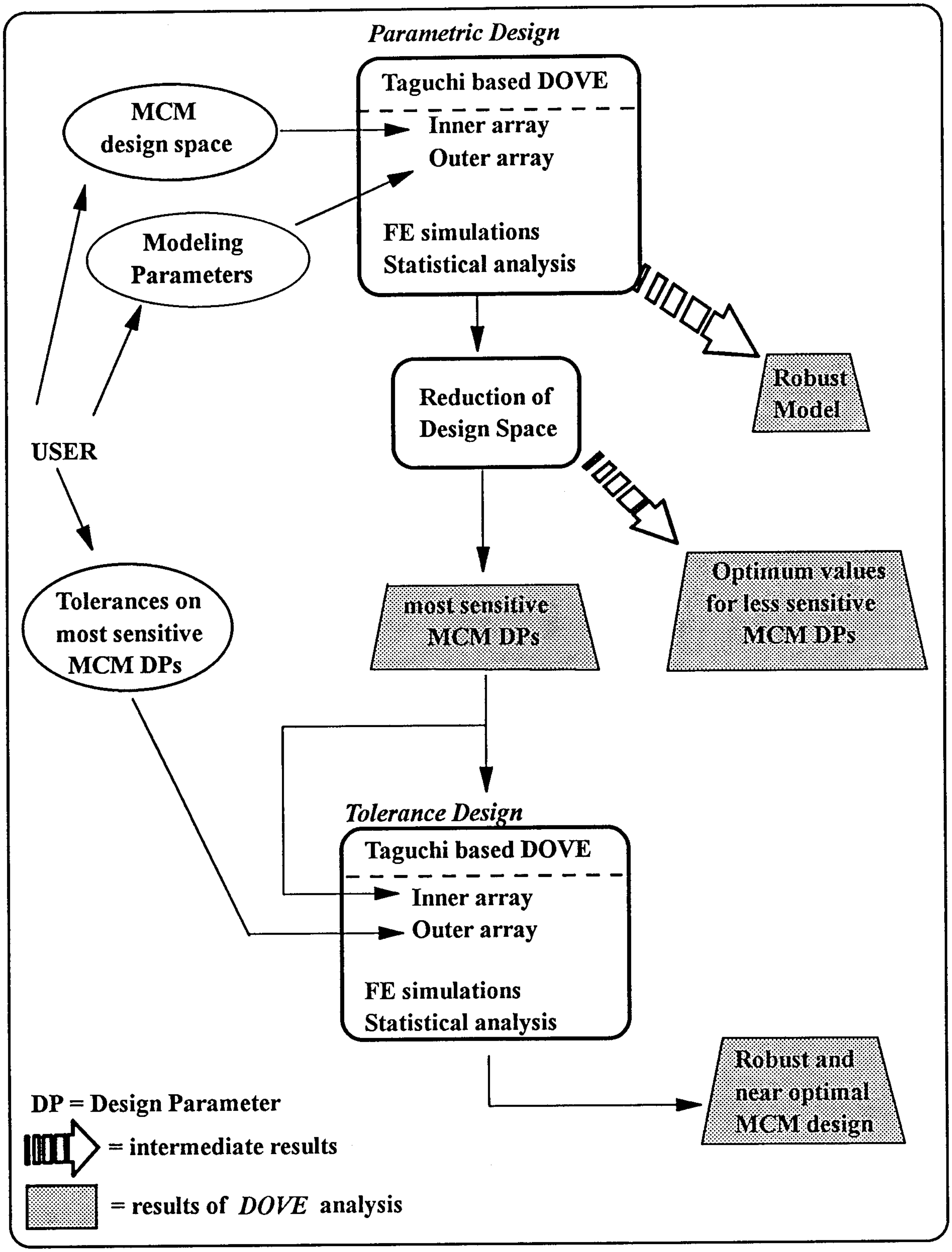

Figure 2: Flowchart of the proposed methodology

Design space reduction: Based on the percent contributions of the MCM design parameters obtained at the end of the previous step, only those parameters to which the performance parameter of the design is (relatively) more sensitive are chosen for a tolerance design. This selection of the sensitive parameters are based on some user specified cut off value for the percent contributions. All the other MCM design parameters are fixed at the optimum levels obtained from the parametric design.

Tolerance design: In this step the effect of tolerances on the sensitive MCM design parameters are investigated to obtain an MCM design that is robust with respect to the above assigned tolerances. At this point, it is necessary to emphasize that all the statistical analysis results of the design of experiments is valid only for the corresponding design space selected by the user and the nature of the numerical simulations (finite element analysis) being used. The finite element simulations do not suffer from any nonrepeatability problems and hence errors due to either the environment or the simulation method that cannot be measured, *do not* exist in the model or analysis. For this purpose the sensitive design parameters are represented in the *inner array* and the tolerances on them are represented in the *outer array*. The arrays define the corresponding virtual experiments which are performed to obtain the performance parameter values. A modified signal to noise (S/N) ratio, different from those suggested by the Taguchi approach (see appendix A), that minimizes both the mean and the variance in the performance parameter is used to obtain a design that has least variation with respect to the tolerances on the design parameters.

The three step approach outlined in this section allows the designer to first generate a robust model that closely represents the physical system, then obtain significant design parameters

affecting the performance of the design and finally investigate the effect of tolerances on these significant design parameters. In this manner a robust MCM package design that is least sensitive to the tolerances on the MCM design parameters is obtained. In addition, the values of the modeling simplification parameters for robust modeling are generated. The design of an MCM example to illustrate the above methodology is presented in Section 7.

To enable effective use of the above discussed methodology and obtain robust and optimal MCM designs, there is a need for a software tool that supports this design methodology. The Intelligent Multichip Module Analyzer (IMCMA) is a computer aided design tool based on a blackboard based system architecture that uses an object oriented data representation and is briefly outlined in Section 4. The following section explains how the design of experiments technique has been implemented into specific software modules and fully integrated into the IMCMA blackboard-based modeling system.

3.3 Design Of Virtual Experiments (*DOVE*)

*D*esign *Of* *V*irtual *E*xperiments *(DOVE)* is a methodology to study the design quality of MCM packages by rapid comparative evaluations of candidate MCM package designs. The methodology uses the Taguchi-based Design of Experiments (DOE) technique, which minimizes the number of experiments required to sample the entire design space. Based on a user-defined MCM package design space consisting of design variables and their levels, input via a graphical user interface (GUI), a set of finite element thermal simulations are performed. Since these are computer simulations, they are referred to as *virtual* experiments in contrast to *real* experiments. The design quality of one MCM package device relative to another is assessed in terms of the maximum temperature in the package that correlates with the thermo-mechanical performance of

the device. A statistical-based analysis is performed on the maximum temperatures obtained from the experiments and the results are graphically represented in the form of pie, bar and xy graphs and an ASCII file with the extension "dove."

It should be noted that at the present stage of development the evaluation of the MCM design electrical design issues are not being considered. The near optimal MCM package design is based purely on the thermal performance of the MCM. In reality, electrical performance issues are critical in deciding on the optimality of a MCM design. Robust MCM design based on electrical design parameters using Design of Experiments techniques is discussed by Iqbal [12]. The author outlines the application of use of Response Surface Analysis which is a type of DOE technique to obtain robust electrical MCM designs. Electrical performance was evaluated in terms of signal propagation characteristics. This work clearly demonstrates the applicability of the methodology being proposed in the report for mechanical (thermal) design and how it can be easily extended to electrical design. Thus, the proposed Design of Virtual Experiments methodology can be extended to include one or more metrics related to electrical performance of the MCM. In this regard MCM routing tools or wiring heuristics seem most appropriate to evaluate a particular MCM package design, since the values of the MCM package design parameters will strongly affect how the MCM is routed. For this purpose a software system (tool) would be integrated with the existing system (IMCMA) that would evaluate the electrical performance of MCMs based on the geometry, routing and placement information by performing circuit simulations. Such a tool is presented by Liao [13]. This tool developed at INTEL was used for the design of the *i*486TM[1] microprocessor based MCM. Electrical computer aided design (ECAD) systems such as this can be interfaced with the existing system (IMCMA) to obtain the electrical

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1 *i*486 is a trademark of Intel Corporation

performance of candidate MCM designs. Integration of such software tools with IMCMA is easily done due to the blackboard based system architecture described in the report. Upon incorporating such tools and adopting the methodology proposed in the report, the design engineer will be able to obtain robust MCM designs based on either electrical and/or mechanical performance.

The ***DOVE*** module is completely integrated into the Intelligent Multichip Module Analyzer (IMCMA) which is built on an object-oriented blackboard based framework of GBB[2] version 3.0. Details of this integration is explained in Section 5. The ***DOVE*** module can be started from the main IMCMA-GUI by sequentially mouse clicking on **"FILE"** and **"Run DOVE"** to bring up the ***DOVE***-GUI window titled "Design of Virtual Experiments."

Some important features of ***DOVE*** are listed below.

- **Design Quality:** Bases quality of MCM on relative thermal behavior which is known to drive thermal-mechanical behavior.
- **Near-Optimum Design:** Identifies "best" MCM package design among possible package designs by performing comparative evaluations instead of absolute evaluations.
- **Inexpensive early design quality evaluations:** Emphasis is placed on rapid exploration of design space by evaluating a fractional factorial set of experiments.
- **Sensitivity Analysis:** Helps identify user-selected design parameters that affect the MCM package design performance **the most**.
- **Robust Modeling:** Allows judicious selection of modeling simplifications by providing an insight into their effects on performance of the MCM design.

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[2] GBB is a registered trademark of Blackboard Technology Group

► **Easily Expandable:** The methodology is applicable to a wide gamut of MCM package configurations (MCM-L, MCM-C, MCM-D) and is easily expandable to future MCM package designs

With the design of experiments methodology, numerous candidate MCM designs can be rapidly evaluated at the early design stage. The most promising of these designs are selected for manufacturing and testing to more accurately estimate the absolute reliability of the MCM design in terms of minimum cycles to failure or MTBF.

For a design space consisting of n design variables, each varying at m discrete levels, the full factorial set of experiments to be performed will be m^n . For example, if n = 13 and m = 3, a total of 1,594,323 experiments will have to be conducted to exhaustively search for the optimum level of each design variable at which the performance parameter of the design configuration is at it's best (lowest or highest, as the case may be). The Taguchi-based DOE technique makes use of orthogonal arrays by which only a fraction of the full factorial set of experiments need to be conducted. By analysing the results the most optimum design configuration can be derived.

An orthogonal array is a matrix of values for the design variables for each experiment. The number of rows and columns signify the total number of experiments to be performed and the total number of user selected design variables respectively. Each cell value in the matrix signifies the level at which a design variable is to be set for an experiment. These values could also be a discretization of a continuous design variable. By choosing an appropriate orthogonal array, only a fractional of the experiments need to be conducted. In the above example where n=13 and m=3 an L27 orthogonal array is selected meaning that only 27 experiments have to be conducted as opposed to 1,594,323 complete set of experiments.

4 Intelligent Multichip Module Analyzer (IMCMA)

IMCMA is a computer aided design **(CAD)** tool that uses the powerful technique of finite element modeling and analysis to rapidly and automatically assess the design quality of MCMs. It is based on a blackboard based system architecture, the basic features of which are shown in Figure 3. A blackboard system is characterized by three major characteristics:

- Problem solving is performed by cooperating knowledge sources (KS) which are numeric software codes or information sources such as the human being.
- The KSs interact anonymously using a global, shared and structured database called the *blackboard.*
- Problem solving is directed by a flexible control component that is separate from the KSs. Signals called *events* form the interface between the control shell and the blackboard. Events trigger KSs.

IMCMA fully supports object class libraries for MCM devices, device components (substrate, well, interconnect lead etc.), and materials. IMCMA begins with the initial state of knowledge of MCM provided by the user which consists of a very simple mechanical description of the system. Upon completion, the engineer receives from **IMCMA** the final state of knowledge which is the thermo-mechanical performance of the MCM design.

Conventional finite element codes lack high level, rich representations of designs and environments. Domain-specific features such as wells, interconnects, substrate etc. are absent and therefore feature-specific design, modeling and analysis knowledge cannot be represented in existing finite element codes. The user builds the finite element model using featureless geometric

entities and geometric construction techniques. Accordingly, the process of developing the finite element model is a time consuming activity.

When a physical system is represented by a solid model on a computer, the representation is only an abstraction of the actual system. This high level representation in the computer that contains details that closely defines the physical system is considered to be "rich" in information. A finite element model defined in terms of elements, nodes and boundary conditions is termed as low level representation. This is because the information comprising the finite element model is inherited from the properties of the high level information. Depending on the operation being performed on the physical system, different features of the part details are required. Hence, without the ability to represent designs and design components at "rich levels of abstraction," it is difficult for the finite element codes to reason about the important abstract design and manufacturing related knowledge for automation purposes.

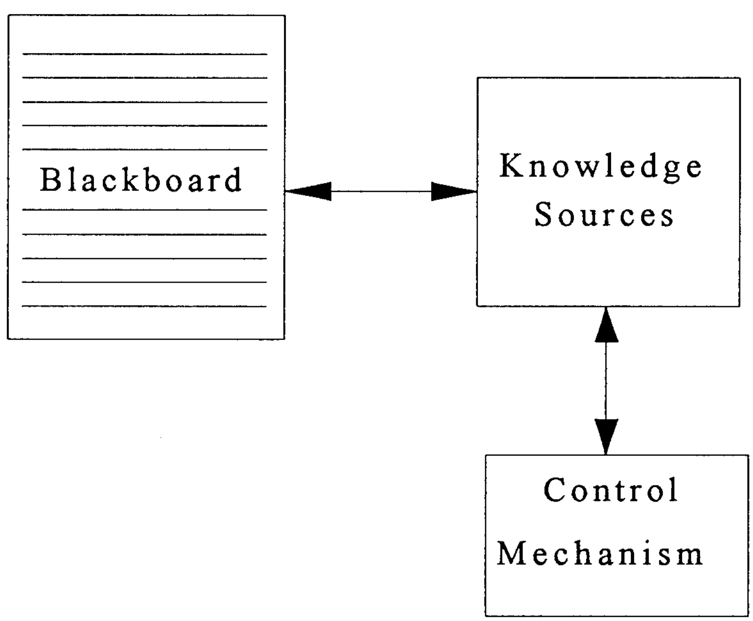


Figure 3: Blackboard based system architecture

The above drawbacks of commercial finite element codes are overcome in **IMCMA.** The entire process of Finite Element Modeling and Analysis **(FEMA)** is highly automated. The overall modeling strategy is a high level, object oriented approach which allows the engineer to develop finite element models of MCMs at device or component levels of abstraction. The user does not have to deal with the intricacies of geometry definition, material property specification, element type selection and mesh generation typically required for a finite element analysis **(FEA)** using commercial finite element packages. Hence, in **IMCMA** the computer based modeling environment occurs at a natural or engineering level of abstraction. To estimate the design quality, all the user needs to input into **IMCMA** is a basic layout representation of the MCM. **IMCMA** automatically converts it into a finite element model, performs analysis and returns the quality of the design. The **IMCMA** system is shown in Figure 4.

Other advantages of IMCMA are the object libraries and the object connectivity information. The object libraries enable the user to model MCMs with different materials and component configurations by simply selecting them from the appropriate object libraries. Object connectivity facilitates quick data retrieval. Thus, the user does not have to search large static data files or even through dynamic blackboard for required information related to the object.

Explicit representation of object relationships also facilitates finite element modeling and analysis efforts. For example, in microelectronic devices interconnects often play a critical role in the overall reliability of the device. However, their range, number and minute sizes prohibit their inclusion in the large scale finite element model of the device. Lacking super computer resources, the engineer must adopt a top down hierarchical modeling strategy in which a small scale finite element analysis of a particular interconnect is obtained by a succession of larger scale to smaller

scale models, a process called "submodeling" in the FEA community. In effect, the modeling strategy represents a mathematical "zooming in" to the critical interconnects. In IMCMA the finite element model is represented by element and node objects in the blackboard which have relational links to the material, component, and device objects. In this way analysis results (i.e. temperature, stress and strain), are associated with high level MCM objects and are thus easily transferred as boundary condition information for subsequent submodeling of microfeatures.

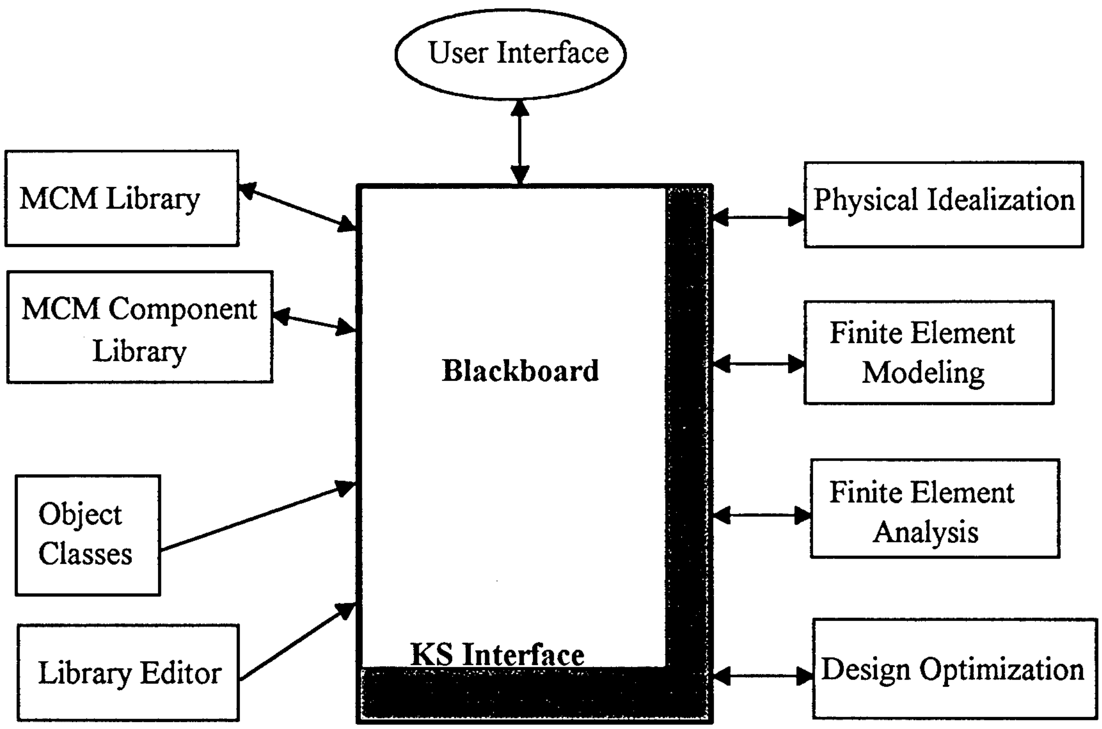
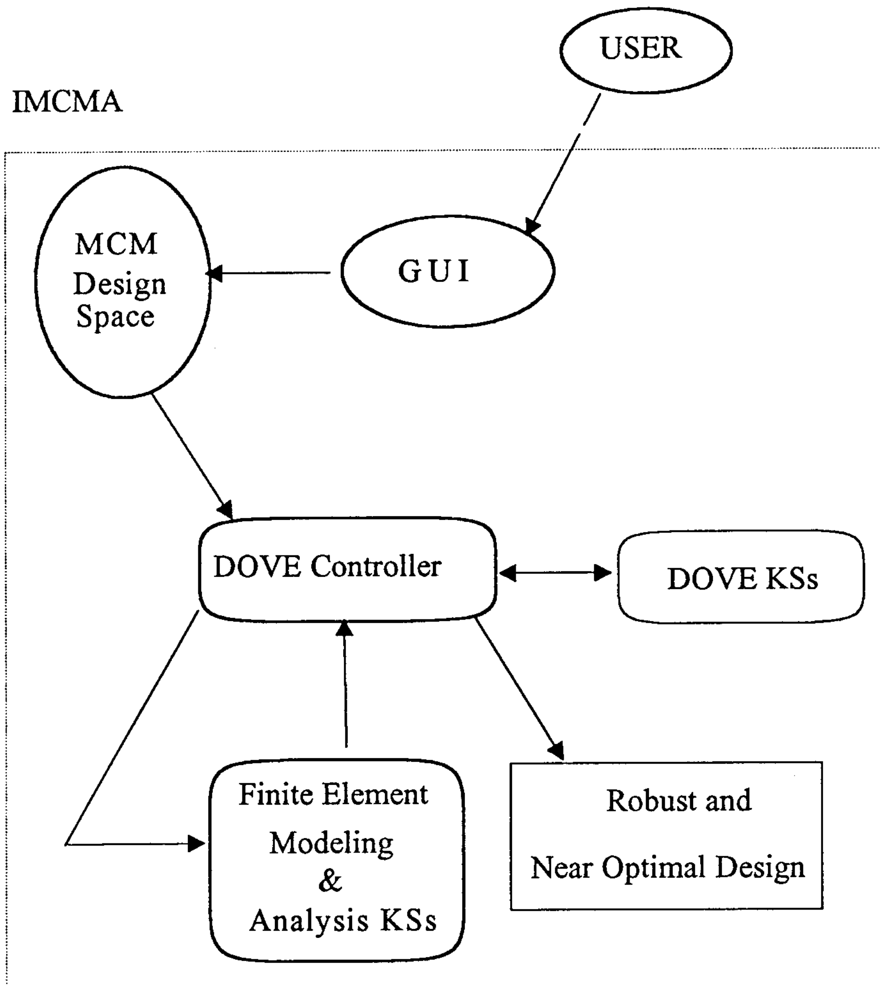


Figure 4: The IMCMA system

5 Integrating *DOVE* with IMCMA

The *DOVE* KSs consist of knowledge sources which perform the appropriate virtual experiments and statistical analysis on the performance data, for the given design space. The interaction of the design optimization KS with the rest of IMCMA system is schematically represented in Figure 5. The *DOVE* controller controls the execution of the various *DOVE* KSs

and the finite element modeling and analysis KSs. Thus the IMCMA system performs an efficient search of the design space and evaluates the performance of candidate MCM designs to obtain a robust and near optimal MCM design.



GUI: Graphical User Interface
DOVE: Design of Virtual Experiments
KSs: Knowledge Sources

Figure 5: Design optimization KSs within IMCMA system

The parametric design of the proposed methodology has been completely integrated into the IMCMA system. Three different unit classes were defined in the ***DOVE*** module to represent the various ***DOVE*** objects so as to be consistent with the object oriented data representation within

IMCMA. Since all the procedural steps in the *DOVE* module are sequential in nature, simple functions are used analogous to knowledge sources. The following sections briefly describes the unit classes used in the *DOVE* module. The various files containing the knowledge sources/functions written in Common Lisp are briefly described in appendix B.

5.1 Unit Classes in *DOVE*

The various unit classes in *DOVE* and brief descriptions of each of them are listed below.

1. Design-Variable Unit Class

   All the design variable objects belong to this unit class which has the following slots defined.

   Component-name - stores name of component that the design variable belongs to

   DV-number - stores the number of the design variable

   DV-attr - stores the attribute of the design variable ie. location-x, size-w etc.

   DV-type - stores whether the design variable is physical or non-physical

   Levels - stores the number of discrete levels

   Level-values - contains a list of values of the design variable at each level

   The dimensional index and the path for this unit class are *DV-number* and (model design-variable) respectively

2. Orthogonal Array Unit Class

   This version of *DOVE* has 8 standard orthogonal arrays (OAs). Additional orthogonal arrays can be easily added by simply editing the file OAS.LISP. Among the eight OAs, five of them are level-2 arrays (viz. L4, L8, L12, L16 and L32) and three are of level-3 arrays (viz. L9, L18 and L27). The slots defining each OA are:

OA-name - name of the array e.g., L27

levels - number of levels

max-factors - maximum number of design variables that the OA can represent

total-number-of-VEs - total number of virtual experiments

total-number-of-DVs - total number of design variables defined in the current design-space

array - the matrix of design variable levels for each virtual experiment

The dimensional indices for this unit class are *levels, max-factors* and *OA-name*.

3. Design Space Unit Class

This unit class has been defined to facilitate conducting multiple sets of ***DOVE***s by defining unique configuration designs as different instances of the Design Space unit class. With minor modifications in this version of ***DOVE***, a series of parametric designs can be tested and analyzed for different configurations designs. The different slots in this unit class are:

DS-name - the name of a specific configuration design

total-DVs - total number of design variables

number-of-levels - the number of discrete levels of the virtual experimentation

performance-parameter - the parameter by which the design performance is evaluated

5.2 The *DOVE* GUI

The ***DOVE*** GUI has been built using Chalkbox tools which are a standard part of GBB version 3.0. The ***DOVE*** GUI can be invoked by sequentially clicking on the "FILE" and

"RUN-DOVE" buttons of the main IMCMA-GUI. Before invoking the ***DOVE*** GUI, a model file containing the base configuration of a MCM package should be loaded by sequentially selecting "FILE," "OPEN" and then the corresponding file from the main menu of IMCMA-GUI.

The ***DOVE*** GUI first searches the current blackboard database and displays the list of components of the current model loaded. Shown below in Figure 6 is a schematic drawing of the ***DOVE***-GUI after an example file consisting of 3 chips mounted on a substrate is loaded. A brief description of the various GUI buttons follows.

In this version of ***DOVE*** module, the following parameters can be selected as design variables.

- Location-x (bottom-left x-location of chip components)
- Location-y (bottom-left y-location of chip components)
- Size-L (length of substrate component)
- Size-W (width of substrate component)
- Size-Z (thickness of substrate component)
- Material properties of component materials
- Materials for components

Defining a design-variable: The following are sequence of menu buttons to be selected when defining a design variable

- Choose component by clicking with the mouse on components listed in upper-left window of the ***DOVE***-GUI
- Click on **"SELECT"** to select the component

- A window pops up listing parameters of the component that can be chosen as design variables. Click on the parameter to select it as a design variable.
- For selected design variable, enter low and high values into appropriate widget
- Click on **"OK"** to complete the definition of the design variable

Each design variable successfully defined as above will be represented as shown in right top window titled DESIGN-SPACE. Figure 7 pictorially shows the typical steps taken by a user while defining a design variable.

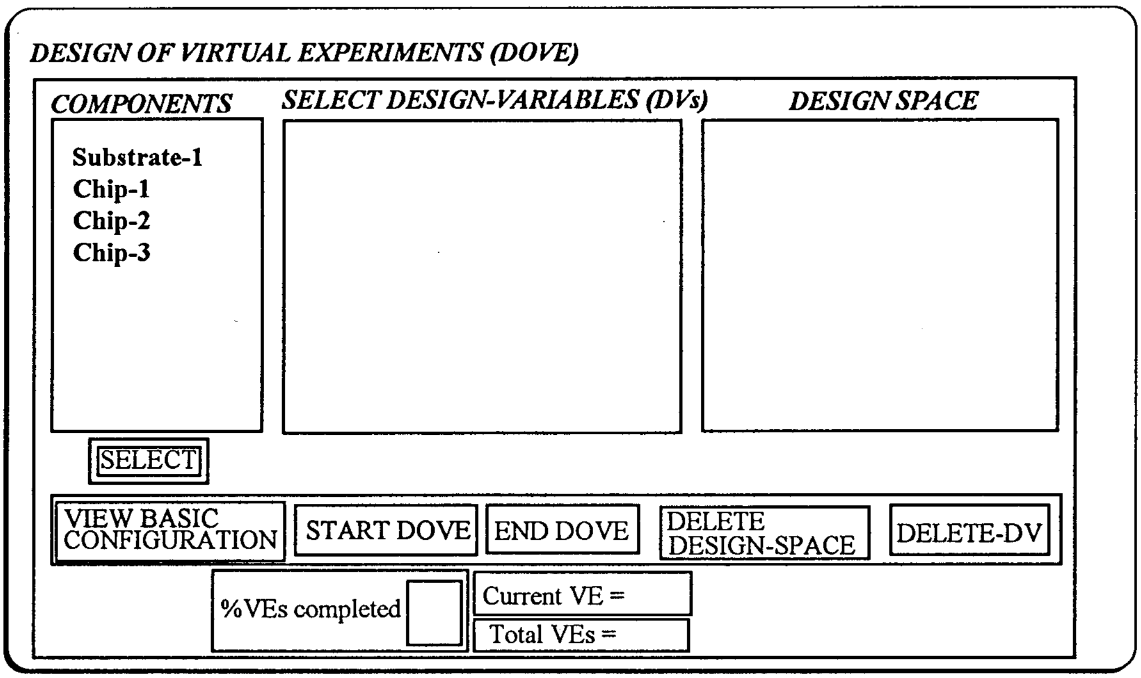


Figure 6: Schematic drawing of the *DOVE* GUI

SELECT	After choosing the component to be selected, click here to select the component
VIEW BASIC CONFIGURATION	Click to view the basic MCM configuration. Consequently, an inspection of any component can be made by clicking on the component in the basic configuration window
DELETE-DV	After choosing a single design variable (DV), click here to delete it from the design-space
START DOVE	Click here to start the Taguchi-based design of virtual experiments. To be done after all the desired design variables have been defined

END DOVE	Click here to exit the design of virtual experiments module
DELETE DESIGN SPACE	Click here to completely erase the design-space and start a new set of design space definition
% VEs Completed	Displays percentage completion of virtual experiments
Current VE =	Displays current virtual experiment being performed
Total VEs =	Displays total number of virtual experiments

The sequential steps of ***DOVE*** are as follows.

- User selects design variables and their values at each level to form the design space using a Graphical User Interface (GUI).
- An appropriate orthogonal array that closely maps onto the design space is selected from the list of arrays in the database.
- The parameters of components corresponding to each design variable are updated based on the cell values of the selected orthogonal array for the current virtual experiment.
- After updating all component parameters, the new MCM package design configuration is modeled and analyzed by the various finite element based knowledge sources.
- From the results of the numerical simulation, the complete mesh geometry data and the maximum nodal temperature are saved before the next experiment starts.
- Steps 3, 4 and 5 are repeated for all the experiments.
- After completing all virtual experiments, a statistical analysis is performed on the list of performance parameter values (maximum nodal temperature).

- The results of the statistical analysis are graphically represented in the form of pie-, bar- and xy graphs and are also written out in ASCII format into a file with the extension ".dove."
- The "mean level" of a design parameter at a particular level is evaluated by averaging the performance parameter values of all virtual experiments having the design parameter value set at that particular level. From all these mean levels, the optimum design configuration is predicted. This optimum design configuration may or may not be the same as one of the experiments already performed. Hence, if necessary, a confirmation test is performed to compare the performance parameter with the predicted value.

In the current version of ***DOVE*** only 2 level orthogonal arrays are used and hence only a low and a high value for each design variable are to be entered. Secondly, only main effects of design variables are considered. All interaction effects are confounded with the main effects, and thus assumed to be insignificant.

For the example file mentioned earlier, and the design space defined as shown in Figure 7, the postprocessing results of ***DOVE*** are graphically represented as shown in Figure 8. The first plot is a pie graph of percent contributions of each design variable to the performance parameter. The second is a table of the user-defined design space. The third plot is a bar graph of performance parameter versus virtual experiment number and the fourth plot is an xy graph of the mean levels versus the levels of each design variable. This plot represents the sensitivity of performance parameter to the design variable level values.

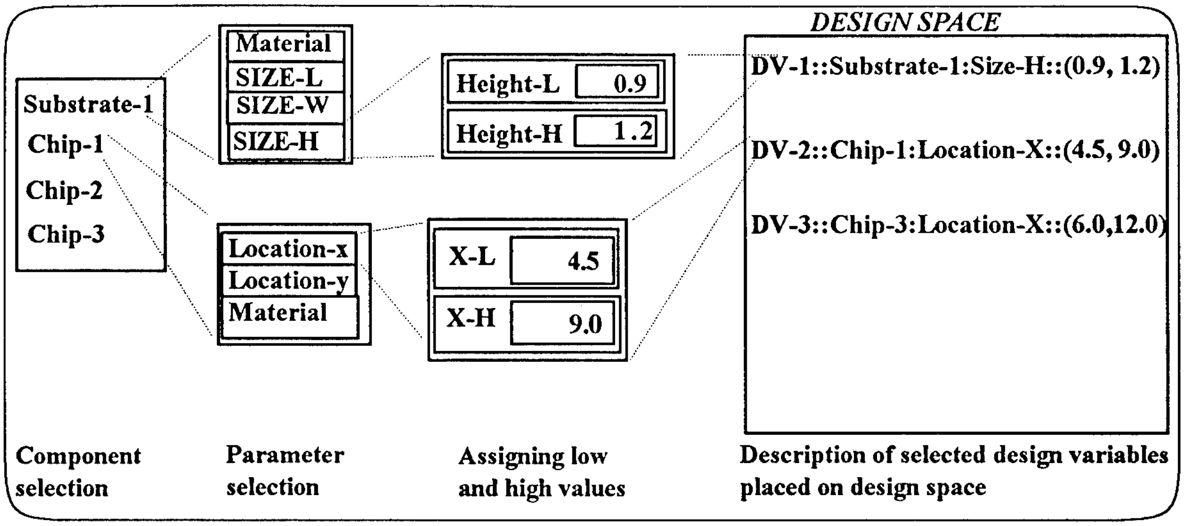


Figure 7: Schematic flowchart showing the steps for defining design variables for an example MCM package using DOVE GUI.

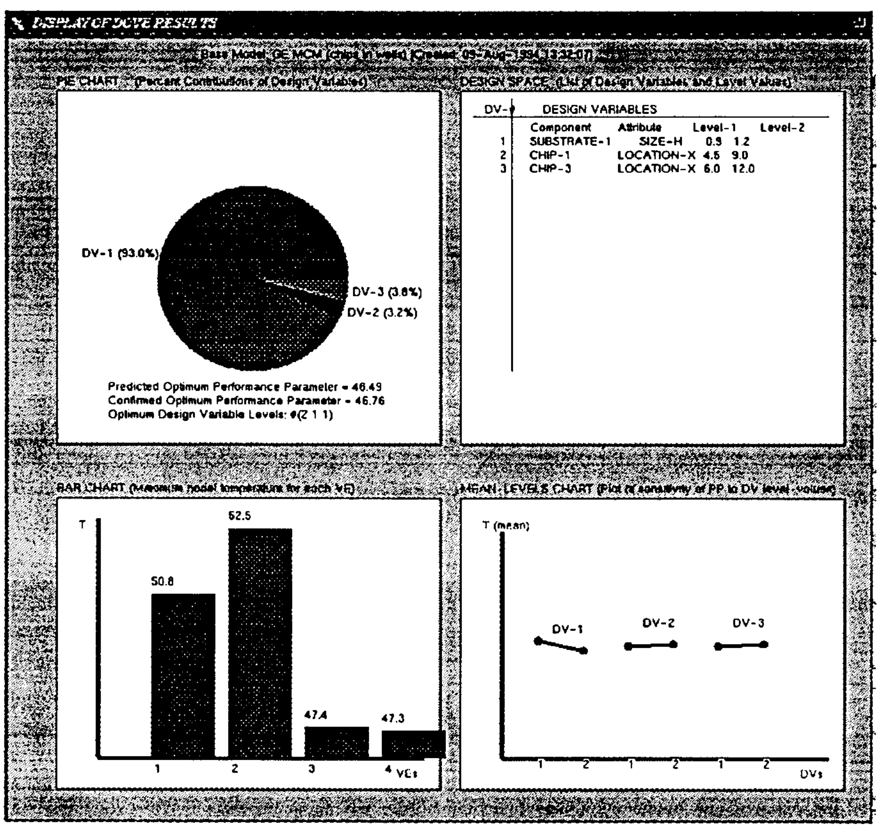


Figure 8: The postprocessing results of the design of virtual experiments for a simple example MCM

6 Validation of *DOVE*

The supporting arguments made in Section 5 for rapid design assessment of MCM packages by using the *DOVE* methodology are validated by conducting two separate sets of experiments. One set consists of a full factorial set of experiments and the other a fractional factorial set. The fractional factorial set is formed by mapping an appropriate orthogonal array onto the selected design space. The maximum temperature in the MCM is chosen to be the performance parameter. It is to be noted that all interactions between the design variables are confounded with the main effects, and consequently, only main effects are investigated. An example MCM package very similar to the one shown in Figure 9 was chosen to demonstrate and validate the *DOVE* methodology with the only difference being the placement of chips. For the validation example, the chips were mounted on top of the substrate, and the thermal flux entering the system via chips seven and three was increased.

6.1 Examples

Only the macro model of the MCM package is chosen for validation. No interconnects, adhesive layers and other micro-components were included in the model. Two sets of design spaces, one with three design variables and the other with seven design variables, were selected as shown in Table 1.

In Set I that has three design variables, a full factorial set will have a total of 8 (2^3) experiments. This set is an exhaustive combination of all possible values for each design variable. By the technique of Taguchi based design of experiments, an L4 orthogonal array is selected to represent only main effects of the design variables. With this L4 array, only four experiments need

to be performed. The maximum temperature in the MCM package was selected as the performance parameter of the MCM package designs.

For the design space Set II which has seven design variables, an L8 orthogonal array is automatically mapped onto the design space resulting in just 8 experiments by the fractional factorial method. This is in sharp contrast to a total of 128 (2^7) experiments by the full factorial method.

Table 1: DESIGN SPACE SETS I AND II FOR THE VALIDATION EXAMPLES

	DV-#	Component	Attribute	Level-1	Level-2
Set I	DV-1	Substrate-1	Size-H	1.2	1.5
	DV-2	Chip-7	Location-X	2	33
	DV-3	Chip-3	Location-Y	8.5	14
Set II	DV-1	Substrate-1	Size-H	1.2	1.5
	DV-2	Chip-1	Location-X	17.62	25.62
	DV-3	Chip-2	Location-Y	21.81	32.64
	DV-4	Chip-3	Location-Y	8.35	14.46
	DV-5	Chip-7	Location-X	2	33
	DV-6	Chip-8	Location-X	23.1	25
	DV-7	Chip-10	Location-X	23	27.3

6.2 Results

The results of validation of the ***DOVE*** methodology are tabulated in Tables 2 and 3. The economical and effective MCM design evaluations using the ***DOVE*** can be clearly inferred from these results.

Referring to Table 2, with only three design variables (Set I) there is a reduction of 50% in the total number of experiments and consequently a same amount of reduction in the computation time. It is to be noted that with the fractional factorial experimentation the predicted optimum

design configuration is the same as obtained as a result of a full factorial experimentation. Due to the optimum design configuration being the same from both the methods, the optimum performance parameter (maximum temperature in the MCM) will also coincide. The predicted maximum temperature is very close to the confirmation value and the small difference between them is attributed to the prediction algorithm that is based on only a fraction of the total number of experiments

Table 3 clearly shows an excellent convergence of the optimum MCM design configuration with only a fraction of the experiments being performed. It is to be noted that with a 94% reduction in the total computational time (using the fractional factorial method), the results of the statistical analysis very closely coincides with a full factorial set of experiments. By performing statistical analysis on the results of the two experimentations, the predicted optimum MCM design configuration were (1112211) and (1122212) from the full factorial and fractional factorial experiments respectively. At first glance, it may appear that the two optimum configuration level values are different for design variables three and seven. But looking at the percent contributions of these two design variables (0.01% and 0.03%) towards the performance parameter, they clearly have little or no effect on the performance parameter and hence the two predicted optimum configurations are essentially the same.

From Table 3, the most important conclusion is that for this particular design space, only 6% of the complete set of experiments needs to be sampled to predict the optimum performance parameter and design configuration.

It is to be noted that the total percent variation in the performance parameter is only around 11%, which may not be significant especially in view of uncertainty in material properties, boundary conditions, etc.

Table 2: COMPARISON OF RESULTS OF FULL AND FRACTIONAL FACTORIAL EXPERIMENTATION WITH 3 DESIGN VARIABLES (DESIGN SPACE SET I)

		Full Factorial Experimentation	Fractional Factorial Experimentation
Number of Experiments		2^3 = **8**	**4** (L4 array)
Optimum Performance Parameter (Tmax)		**43.08**°C	Predicted = **43.03**°C Confirmed = **43.08**°C
Optimum Configuration (Level of each DV)		(1 2 2)	(1 2 2) predicted
Total computational time		32 minutes	16 minutes **(50% Reduction)**
Percent Contributions			
	DV-1	34.42	35.61
	DV-2	64.92	64.12
	DV-3	0.48	0.27
Mean Levels			
Level-1	DV-1	44.56	44.53
	DV-2	47.01	46.91
	DV-3	45.71	45.13
Level-2	DV-1	46.61	46.55
	DV-2	44.18	44.18
	DV-3	45.57	45.45

The following section demonstrates the step by step procedure of the proposed methodology discussed in Section 3.2 for an example MCM package design.

Table 3: COMPARISON OF RESULTS OF FULL AND FRACTIONAL FACTORIAL EXPERIMENTATION WITH 7 DESIGN VARIABLES (DESIGN SPACE SET II)

		Full Factorial Experimentation	Fractional Factorial Experimentation
Number of Experiments		2^7 = **128**	**8** (L8 array)
Optimum Performance Parameter (Tmax)		**43.80**°C	Predicted = **43.64**°C Confirmed = **43.82**°C
Optimum Configuration (Level of each DV)		(1 1 1 2 2 1 1)	(1 1 2 2 2 1 2) predicted
Total computational time		616 minutes	39 minutes **(94% Reduction)**
Percent Contributions			
	DV-1	50.33	51.41
	DV-2	0.32	0.3
	DV-3	0.01	0.07
	DV-4	1.28	1
	DV-5	47.37	46.71
	DV-6	0.06	0.07
	DV-7	0.03	0.31
Mean Levels			
Level-1	DV-1	44.99	45.02
	DV-2	45.92	45.97
	DV-3	46.04	46.05
	DV-4	46.14	46.22
	DV-5	46.96	47.06
	DV-6	45.95	46.05
	DV-7	46.08	46.05
Level-2	DV-1	47.01	47.09
	DV-2	46.08	46.13
	DV-3	45.95	46.05
	DV-4	45.86	45.89
	DV-5	45.04	45.05
	DV-6	46.04	46.05
	DV-7	45.92	46.05

7 An example MCM package design

The design problem chosen was to find an optimal, robust and tolerant MCM design based on a design space for each of the design parameters. With the performance parameter chosen to be the maximum temperature in the MCM, the optimal design would be the one with the lowest maximum temperature. The design variable space is evaluated at three levels, thus allowing for analysis of any second order effects in the behavior of the maximum MCM temperature within the ranges of the MCM design parameters chosen. To demonstrate the above application a simple MCM model with ten wells on a substrate was chosen as shown in Figure 9.

This MCM is similar to the RELTECH[3] test vehicle. Two major assumptions made are: i) the volume of each well is completely filled with chips in it, and ii) all the chips in a well are modeled as a single chip. The x-y centroidal coordinates of substrate, well components, their lengths, their widths and depths are given in Table 4. The origin of the x-y coordinate system is at the lower left hand corner of the substrate. The boundary conditions applied are also shown in Figure 9. Thermal analyses were performed (using finite element simulations) to determine the value of the performance parameter (maximum temperature) for each virtual experiment.

The modeling simplification parameters investigated in this example are the XY-adjust and Z-adjust for finite element meshing. These parameters allow the well dimensions to change slightly to facilitate automatic mesh generation and to significantly reduce the total degrees of freedom (DOF), thereby reducing the computational time. The design parameters of the MCM model chosen and their respective levels are shown in Table 5. The modeling simplification

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[3] RELTECH is a Department of Defense (DOD) and NASA program funded by Advanced Research Project Agency (ARPA). The objective of RELTECH is to select MCM technologies with high DOD, NASA and commercial usage and to verify their performance and reliability.

parameters and their respective levels are shown in Table 6. Corresponding to the thirteen design parameters with three levels each, a standard L27 Taguchi orthogonal array was chosen as the inner array. The two modeling simplification parameters at two levels each are represented in an L4 outer array.

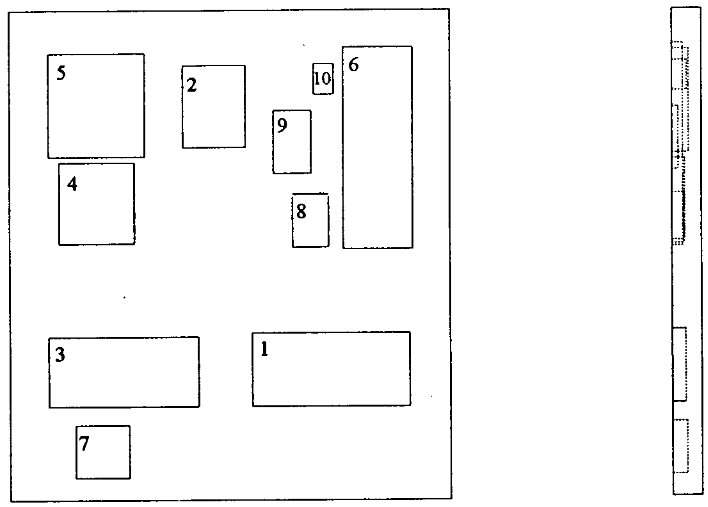

Figure 9: Layout of the example MCM model (10 wells on substrate)
Flux on top surface of all chips except in well-7, q = 1.0 W per well
Flux on top surface of chips in well-7, q = 2.0 W per well
Prescribed temperature on all side surfaces of substrate, T = 35 °F

Table 4: LOCATIONS AND DIMENSIONS (IN MM) OF SUBSTRATE AND WELLS

Component	**X_C**	**Y_C**	**L**	**W**	**D**
Substrate	20.32	20.32	40.64	40.64	1.27
Well-1	30.47	12.2	13	5.99	0.52
Well-2	18.48	31.93	6	6	0.52
Well-3	10.36	11.88	12.99	5.99	0.52
Well-4	9.27	24.81	6	6	0.52
Well-5	9.5	31.93	7.24	7.24	0.67
Well-6	34.02	28.76	6.71	16.78	0.43
Well-7	8	4.69	4.91	4.62	0.36
Well-8	28.14	22.75	3.85	4.95	0.48
Well-9	25.33	30.01	3.42	5.12	0.26
Well-10	28.4	35.03	2.01	2.85	0.57

Table 5: DESIGN PARAMETERS AND THEIR LEVELS (DIMENSIONS IN MM)

	Levels-->		
	Level 1	Level 2	Level 3
Substrate Material (SM)	Cu-AlN K = 0.15 W/mm°C CTE = 2.7 ppm/°C	Cu-Mo-Cu K = 0.17 W/mm°C CTE = 7.5 ppm/°C	SiC-BN K = 0.20 W/mm°C CTE = 4.0 ppm/°C
Chip Material (CM)	GaAs K = 0.05 W/mm°C CTE = 5.7 ppm/°C	Ge K = 0.07 W/mm°C CTE = 6.0 ppm/°C	Si K = 0.13W/mm°C CTE = 2.3 ppm/°C
Substrate thickness (ST)	1.02	1.27	1.52
Location of well-1 (W1)	24.12, 12.20	28.17,12.20	32.14,12.20
Location of well-2 (W2)	18.48, 24.81	18.48, 30.23	18.48, 35.64
Location of well-3 (W3)	10.36, 11.35	10.36, 14.41	10.36, 17.46
Location of well-4 (W4)	5.00, 24.81	8.07, 24.81	11.13, 24.81
Location of well-5 (W5)	5.62, 31.93	8.07, 31.93	10.51, 31.93
Location of well-6 (W6)	34.02, 24.00	34.02, 27.13	34.02, 30.25
Location of well-7 (W7)	4.46, 4.69	20.32, 4.69	36.19, 4.69
Location of well-8 (W8)	25.00, 22.75	26.16, 22.75	27.32, 22.75
Location of well-9 (W9)	24.00, 30.01	25.70, 30.01	27.62, 30.01
Location of well-10 (W10)	24.00, 35.03	26.16, 35.03	28.32, 35.03

Table 6: MODELING SIMPLIFICATION PARAMETERS AND THEIR LEVELS (DIMENSIONS IN MM)

Modeling simplification factors	Levels -------------------------------->	
	Level 1	Level 2
XY-adjust	0	1
Z-adjust	0.06	0.11

First, the parametric design is performed. For this purpose each of the 27 virtual experiments (corresponding to the L27 inner array of design parameters) was run four times with different values of modeling simplification parameters set by the L4 outer array and the values of robust modeling simplification parameters are determined. Next, a screening is done based on the percent

contributions of design parameters at the end of the parametric design step resulting a reduced set of four design parameters . Finally, a tolerance design is performed on the reduced set of design parameters using a three level L9 inner array to represent the design parameters, and a two level L4 outer array to represent the tolerances on them. Thus, a tolerant, near-optimal and robust design is obtained.

8 Results

The results of the virtual experiments and the subsequent statistical analysis performed on these results are tabulated in Tables 7, 8 and 9. Table 7 shows the results of the parametric design, Table 8 shows the reduction in the finite element degrees of freedom (which directly correlates with computation time) due to the robust modeling parameters selected by parametric design and Table 9 shows the results of the tolerance design.

The four columns of results in Table 7 denoted by Max Temp. represent the variation in the maximum MCM temperature in each virtual experiment due to variations in modeling simplification parameters. The *%var* column represents the percent variation in the maximum temperature due to changes in the modeling simplification parameters from one level to the other. The formulas used for computing these variances are presented in the appendix. It can be seen that the variance in maximum temperature due to changes in the modeling simplification parameter values is negligible. With XY-adjust changing from 0.0 to 1.0 the percent variation in the performance parameter, *%var*(xy) is 0.31 and for a change in Z-adjust from 0.055 to 0.110 produced a percent variation (*%var*(z)) of only 0.20 in the performance parameter. This clearly shows that the chosen values of the modeling simplification parameters have little or no significant effect on the finite element solution. Hence, the modeling simplification parameters could be

chosen at any desired level within the ranges tested above. Hence, XY-adjust and Z-adjust were both selected at level 2, i.e., XY-adjust = 1mm and Z-adjust = 0.11mm. This selection was made with an important purpose of minimizing the computational time during the finite element analysis. From Table 7 the column corresponding to the above values of modeling simplification parameters is the virtual experiment set b. This was now chosen as the performance parameter values for a standard Taguchi statistical analysis.

Table 8 clearly shows the effect of changes in the modeling simplification parameters (viz. XY-adjust and Z-adjust) to the finite element modeling in terms of total degrees of freedom which directly correlate to the number of equations to be solved and hence the computational time required for the finite element analysis. The reduction in the finite element total degrees of freedom (computed by comparing the chosen virtual experiment set (viz. b) and the set with the highest value (viz. set a)), was found to be ranging from 67% to 83% which amounts to a significant reduction in computation time.

The optimum levels of the design parameters and their percent contributions were computed and are shown in Table 7. The optimum levels for each MCM design parameter are in the row labeled *opt.* An optimum maximum MCM temperature based on the optimum levels of design parameters was predicted using a prediction formula given by the Taguchi method and was evaluated to be 36.84° F. The optimum temperature obtained on performing a verification experiment setting the design parameter levels at their optimum levels was 38.5° F which is quite close to the predicted value. The percent contributions of the design parameters are shown in figure 10. The reduction of the design space is now done based on the percent contributions obtained in the previous step. Figure 10 shows that substrate thickness (ST) has the maximum

contribution of 47.01%, followed by substrate material (SM) having 24.31%, chip material (CM) having 11.2% and Well 2 (W2) of 5.36%. These are the most significant design factors among the set that was explored and hence are chosen as the design parameters for the next step for tolerance design. During the tolerance design, the levels of all the other less significant factors were fixed at the optimum levels obtained from parametric design.

Tolerance design was carried out with tolerances on the substrate thickness and substrate and chip material properties (ST, SM and CM). The tolerances specified were as follows:

ST: ±2%
SM: ±10%
CM: ±10%

A low tolerance was placed on the substrate thickness since the manufacturing process for substrates can be controlled to tight and accurate specifications while the material properties of substrate and chip materials cannot be determined as accurately. Hence, a tighter tolerance was specified on material properties viz. SM and CM while a relatively loose tolerance was specified on the substrate thickness.

These were represented in an L4 outer array and the design parameters (ST, SM, CM and W2) were represented in a L9 three level inner array. The results of the tolerance design are shown in Table 9. The Taguchi statistical analysis was carried out on the virtual experimentation results (viz. maximum MCM temperature) for determining the levels of design parameters at which both the mean and the variance are reduced. For this purpose a modified signal to noise ratio (see appendix) is used. Based on these values a prediction using the Taguchi prediction formula is performed to predict a design that would have both minimum variation and mean. Using the signal to noise ratio as the performance parameters, the predicted optimum value was evaluated to be 0.12 and the obtained optimum signal to noise ratio was found to be 0.15. The optimum levels for

the design parameters are as shown in the row labeled *opt.* Additional information available from this analysis is the sensitivity of the maximum MCM temperature to the tolerances on the design parameters.

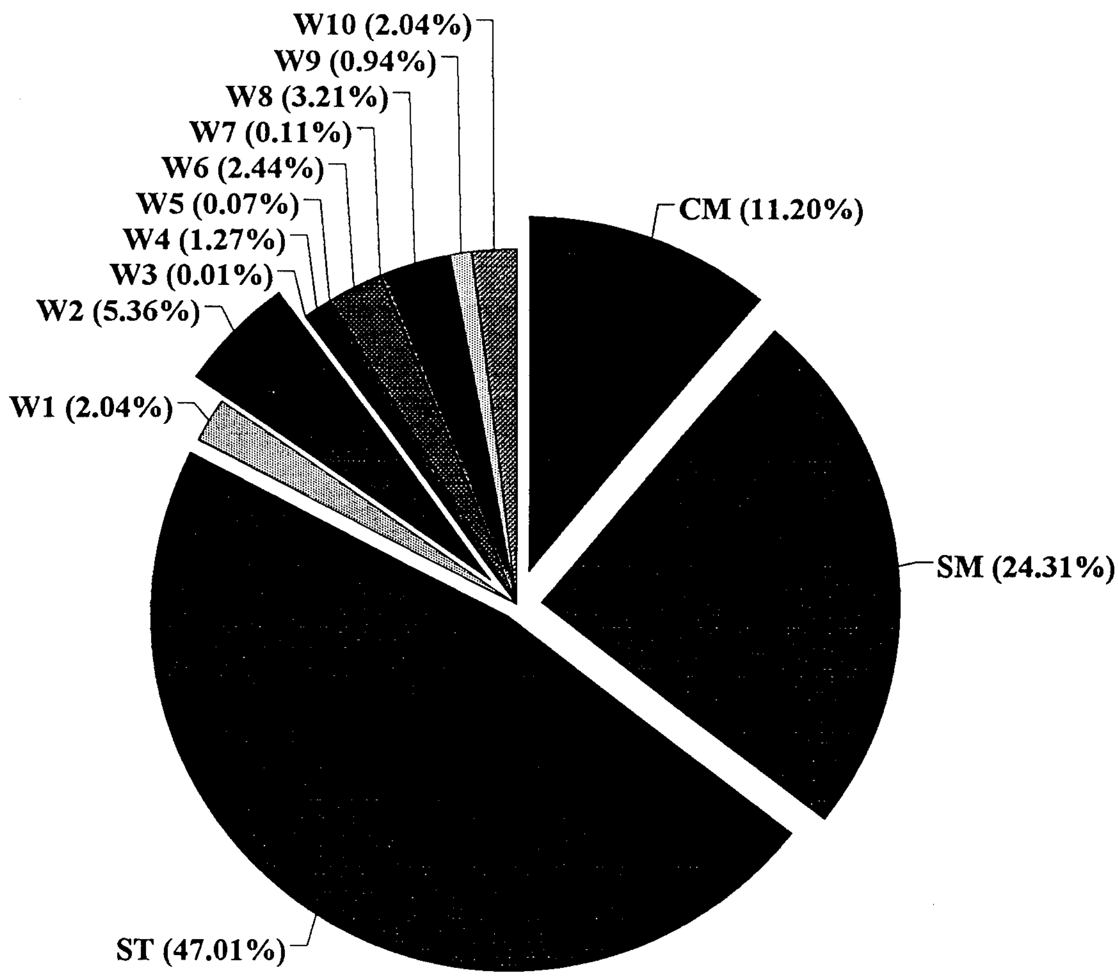

Figure 10: Percent contributions of MCM design parameters to the maximum MCM temperature

Table 7: RESULTS OF PARAMETRIC DESIGN ON THE MCM EXAMPLE

Virtual Experiments (VE): FE simulations (thermal analysis)
Orthogonal inner array chosen: L27 (3 levels) -- 13 MCM design-parameters
Orthogonal outer array chosen: L4 (2 levels) -- 2 modeling parameters
Performance parameter: Maximum Temperature
Performance characteristic: Lower is better

	1	2	3	4	5	6	7	8	9	10	11	12	13					%VAR
														1	1	2	2	
													XY-a	0	1	0	1	**0.31**
													Z-a	0.055	0.11	0.11	0.055	**0.20**
VE#	**Design Factors -->**													**a**	**b**	**c**	**d**	
	CM	**SM**	**ST**	**W1**	**W2**	**W3**	**W4**	**W5**	**W6**	**W7**	**W8**	**W9**	**W10**	**Max. Temp.(F ------------>**				
1	1	1	1	1	1	1	1	1	1	1	1	1	1	**44.24**	**45.01**	**44.12**	**45.14**	
2	1	1	1	1	2	2	2	2	2	2	2	2	2	**44.27**	**43.54**	**44.25**	**43.57**	
3	1	1	1	1	3	3	3	3	3	3	3	3	3	**43.56**	**43.26**	**43.71**	**43.38**	
4	1	2	2	2	1	1	1	2	2	2	3	3	3	**41.61**	**41.51**	**41.53**	**41.58**	
5	1	2	2	2	2	2	2	3	3	3	1	1	1	**41.64**	**41.94**	**41.76**	**42.04**	
6	1	2	2	2	3	3	3	1	1	1	2	2	2	**41.15**	**40.85**	**41.10**	**40.86**	
7	1	3	3	3	1	1	1	3	3	3	2	2	2	**39.84**	**38.90**	**39.77**	**38.97**	
8	1	3	3	3	2	2	2	1	1	1	3	3	3	**39.60**	**39.63**	**39.54**	**39.70**	
9	1	3	3	3	3	3	3	2	2	2	1	1	1	**39.82**	**40.15**	**39.76**	**40.24**	
10	2	1	2	3	1	2	3	1	2	3	1	2	3	**42.22**	**42.05**	**42.16**	**42.11**	
11	2	1	2	3	2	3	1	2	3	1	2	3	1	**41.43**	**41.20**	**41.45**	**41.18**	
12	2	1	2	3	3	1	2	3	1	2	3	1	2	**41.74**	**41.67**	**41.65**	**41.76**	
13	2	2	3	1	1	2	3	2	3	1	3	1	2	**40.26**	**40.34**	**40.29**	**40.41**	
14	2	2	3	1	2	3	1	3	1	2	1	2	3	**40.61**	**40.21**	**40.55**	**40.25**	
15	2	2	3	1	3	1	2	1	2	3	2	3	1	**40.10**	**39.54**	**40.03**	**39.52**	
16	2	3	1	2	1	2	3	3	1	2	2	3	1	**42.70**	**42.24**	**42.59**	**42.38**	
17	2	3	1	2	2	3	1	1	2	3	3	1	2	**41.56**	**41.33**	**41.57**	**41.43**	
18	2	3	1	2	3	1	2	2	3	1	1	2	3	**41.20**	**40.66**	**41.11**	**40.72**	
19	3	1	3	2	1	3	2	1	3	2	1	3	2	**40.66**	**40.57**	**40.64**	**40.59**	
20	3	1	3	2	2	1	3	2	1	3	2	1	3	**40.49**	**40.38**	**40.49**	**40.38**	
21	3	1	3	2	3	2	1	3	2	1	3	2	1	**39.85**	**39.83**	**39.85**	**39.85**	
22	3	2	1	3	1	3	2	2	1	3	3	2	1	**42.65**	**42.00**	**42.03**	**42.84**	
23	3	2	1	3	2	1	3	3	2	1	1	3	2	**41.92**	**41.89**	**41.88**	**41.93**	
24	3	2	1	3	3	2	1	1	3	2	2	1	3	**41.45**	**40.14**	**41.47**	**41.14**	
25	3	3	2	1	1	3	2	3	2	1	2	1	3	**40.18**	**40.10**	**40.21**	**40.14**	
26	3	3	2	1	2	1	3	1	3	2	3	2	1	**40.05**	**40.11**	**40.08**	**40.10**	
27	3	3	2	1	3	2	1	2	1	3	1	3	2	**39.68**	**39.77**	**39.64**	**39.80**	
													AVG	**41.28**	**41.07**	**41.23**	**41.19**	

Optimum Levels of MCM DPs (using marginal means):

opt	3	3	3	3	3	1	1	1	3	3	2	2	3

Predicted Optimum Max. Temperature = 36.84F

Verified Optimum Max. Temperature = 38.50F

Table 8: COMPARISON OF FINITE ELEMENT TOTAL DEGREES OF FREEDOM

	DOF ------>				
ve #	a	b	c	d	%Reductio
1	2067	396	1080	762	80.84
2	2318	390	1200	768	83.18
3	2184	462	1140	909	78.85
4	2087	540	1080	1054	74.13
5	2299	546	1200	1061	76.25
6	2272	462	1200	903	79.67
7	2082	504	1080	986	75.79
8	2288	540	1200	1045	76.40
9	2314	468	1200	917	79.78
10	2088	672	1080	1296	67.82
11	2292	495	1200	978	78.40
12	2340	495	1200	979	78.85
13	2092	588	1080	1140	71.89
14	2298	390	1200	773	83.03
15	2308	576	1200	1132	75.04
16	2078	585	1080	1132	71.85
17	2256	462	1200	896	79.52
18	2191	429	1140	841	80.42
19	2066	576	1080	1122	72.12
20	2312	450	1200	885	80.54
21	2274	630	1200	1211	72.30
22	2074	429	1080	844	79.32
23	2314	495	1200	985	78.61
24	2203	585	1200	1140	73.45
25	2064	540	1080	1058	73.84
26	2318	462	1200	914	80.07
27	2316	585	1200	1135	74.74

ve#: virtual experiment due to MCM design parameter
DOF: Finite Element Degrees of Freedom
a: for XY-adjust = 0.0mm and Z-adjust = 0.055mm
b: for XY-adjust = 1.0mm and Z-adjust = 0.110mm
c: for XY-adjust = 0.0mm and Z-adjust = 0.11mm
d: for XY-adjust = 1.0mm and Z-adjust = 0.055mm
%Reduction: percent reduction in DOF = ((Max(a,c,d) - b)/Max(a,c,d))*100

Table 9: TOLERANCE DESIGN ON REDUCED MCM DESIGN SET

Virtual Experiments (VE): FE simulations, thermal analysis
Orthogonal inner array chosen: L9 (3 levels) -- 4 MCM design-parameters
Orthogonal outer array chosen: L4 (2 levels) -- 3 tolerance parameters
Performance parameter: Maximum Temperature
Performance characteristic: Lower is better

	1	2	3	4					
					%tol(ST)	-2%	+2%	+2%	-2%
					%tol(SM)	-10%	+10%	-10%	+10%
					%tol(CM)	-10%	-10%	+10%	+10%
VE#	**Design Factors ------------------------------------**					**a**	**b**	**c**	**d**
	CM	**SM**	**ST**	**W2**		**--- Max. Temp.(F) ------------------>**			
1	1	1	1	1		**44.34**	**42.62**	**43.67**	**42.65**
2	1	2	2	2		**41.57**	**40.41**	**41.09**	**40.37**
3	1	3	3	3		**39.72**	**38.95**	**39.35**	**38.86**
4	2	1	2	3		**41.63**	**40.44**	**41.17**	**40.43**
5	2	2	3	1		**40.57**	**39.59**	**40.18**	**39.56**
6	2	3	1	2		**41.82**	**40.58**	**41.32**	**40.58**
7	3	1	3	2		**40.42**	**39.86**	**40.10**	**39.43**
8	3	2	1	3		**41.71**	**40.41**	**41.26**	**40.49**
9	3	3	2	1		**40.15**	**39.20**	**39.81**	**39.22**
opt	**3**	**3**	**3**	**3**	**opt-run**	**38.89**	**38.18**	**38.75**	**38.3**
					avg(1..9)	**41.33**	**40.23**	**40.88**	**40.18**

Statistical Analysis on DVs:

opt	**3**	**3**	**3**	**3**

Predicted OPT-Ratio: 0.12
Verified OPT-Ratio: 0.15

These sensitivity values are obtained by taking the mean values for each column of results labeled a, b, c and d and performing a standard Taguchi statistical analysis treating these mean values as outputs of the four virtual experiments of the L4 outer array. The percent contributions of the pruned MCM design parameters and those due to the tolerances on them are shown in Figure 11.

From this figure it can be clearly seen that while the maximum MCM temperature is very sensitive to the values of substrate thickness (ST) (65%), it is most sensitive to the tolerances on substrate material (SM) (89%) rather than the tolerances on substrate thickness (ST) (6%). A mesh plot of the near-optimal and tolerant design obtained is shown in Figure 12. The left bottom part of Figure 12 shows the finite element mesh plot of the MCM with the top surface temperature of the elements in color (red denotes hottest region). The optimum maximum MCM temperature obtained was 38.18°F with the finite element mesh having only 495 total degrees of freedom.

In summary, at the end of the three step procedure we can draw the following conclusions for this specific test case MCM design space:

1. For near-optimal, tolerant design the levels of design parameters are:

   SM, CM, ST, W1, W2, W6, W7, W10 all at Level-3

   W3, W8, W9 all at Level-2 and W4, W5 at Level-1

2. Robust modeling simplification parameter values are:

   XY-adjust: 1.0 mm, Z-adjust 0.11mm

3. Significant reduction in computation time using above modeling simplification parameter values (77%)

4. Maximum MCM temperature is most sensitive to the substrate thickness (ST) and tolerances on substrate material (SM).

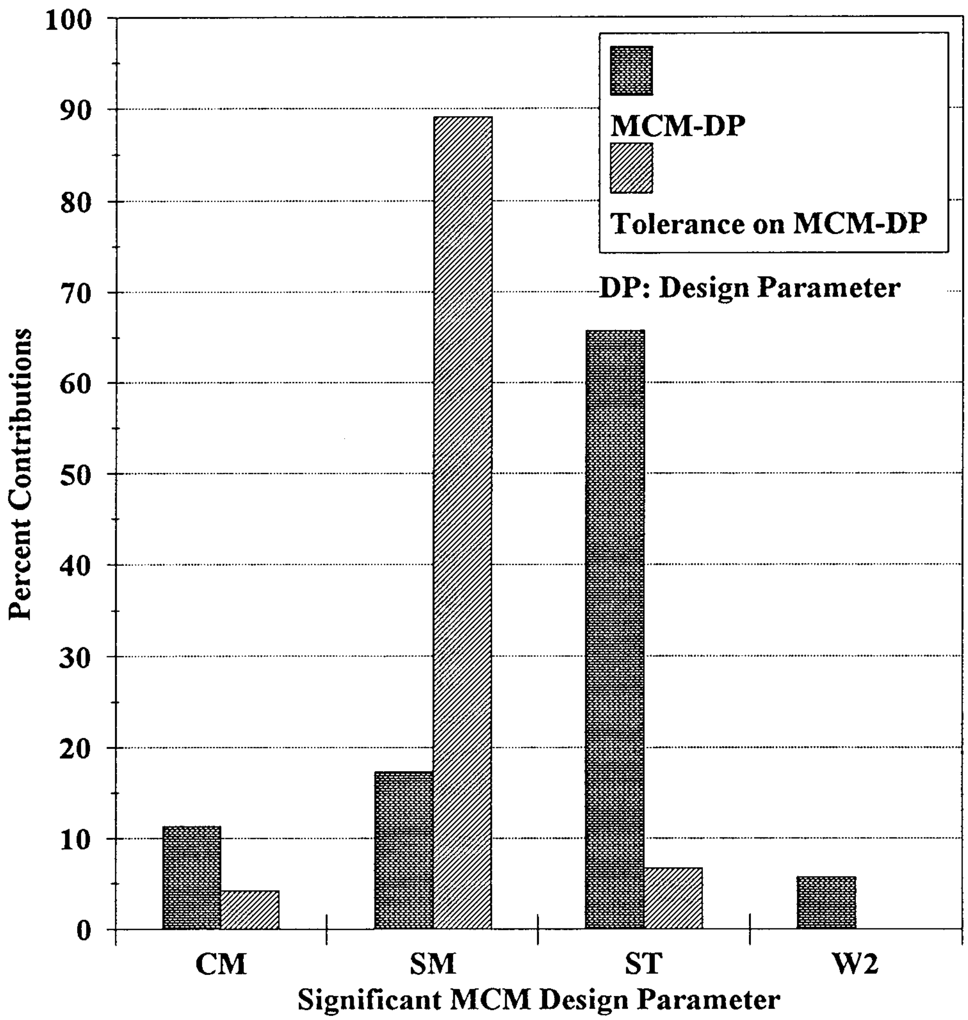

Figure 11: Percent contributions of sensitive MCM design parameter values and their tolerances.

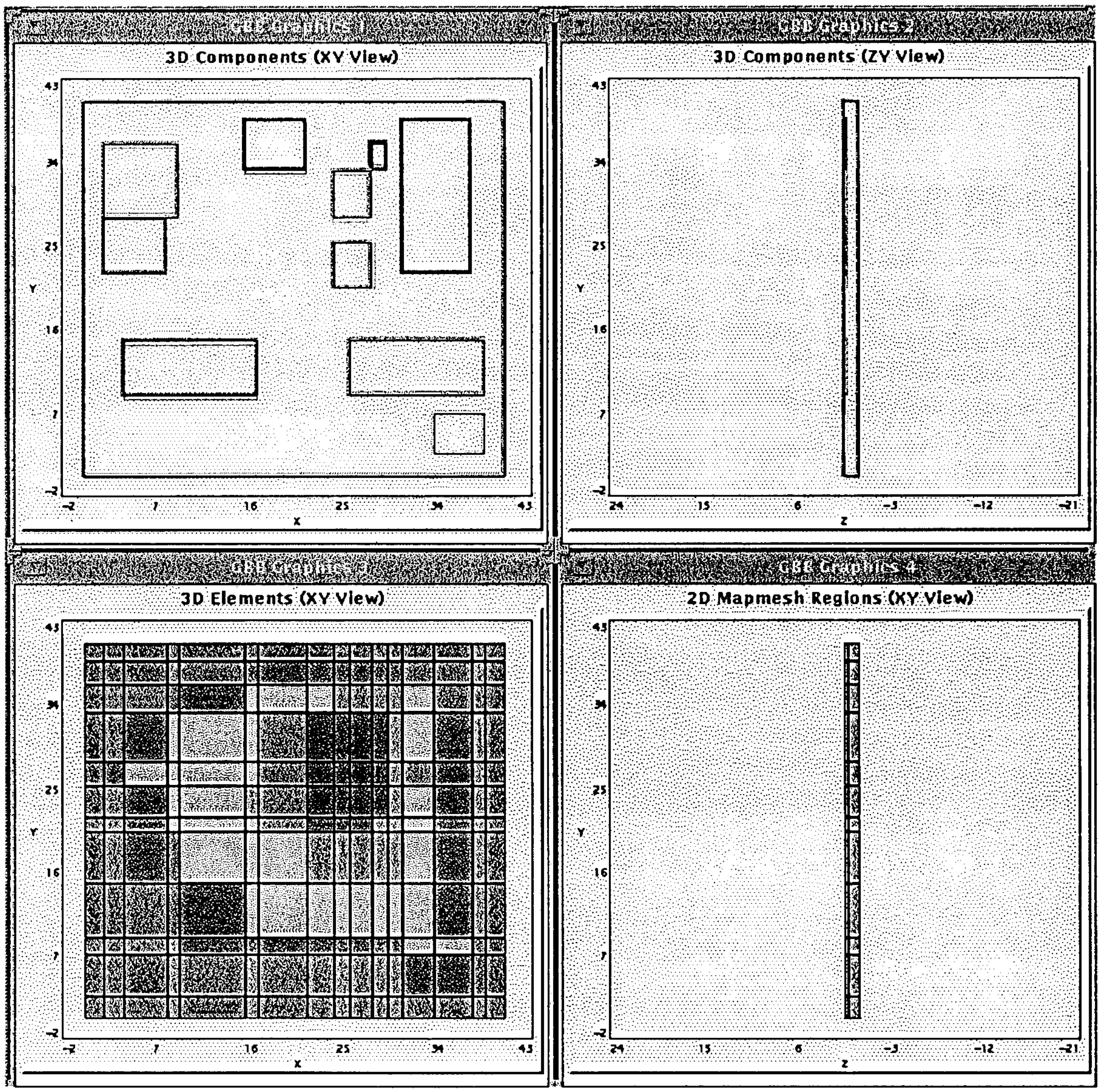

Figure 12: Finite element mesh plot of the optimum MCM package design.

9 Conclusions

The above example demonstrates an application of the proposed methodology for an MCM design. An efficient methodology for robust modeling and tolerance design has been developed using a DOE technique. This methodology enables a rapid and efficient pruning of the design space and the identification of significant design factors affecting the performance. It also facilitates robust modeling by judicious selection of modeling simplification parameters which also directly affect the speed of finite element simulations. Finally, the proposed methodology allows the designer to investigate the effect of design parameter tolerances on the performance of the design.

The proposed methodology can also be applied to microfeatures of MCMs, such as interconnects, die features, etc. by "zooming in" from a macroscopic model to a microscopic model in a sequential multistep analysis procedure called finite element submodeling. Ongoing research is focused on this area [4].

10 Limitations and Future Extensions

At present, the user is allowed to choose only 2 levels for each design variable, thereby accounting for only a linear behavior of the performance parameter with respect to the DV. The *DOVE* code can be easily modified to include a 3 level input for each DV so that a quadratic behavior, if any, can be investigated.

In the present version of *DOVE*, only the main effects of the design variables are investigated. No interactions among them are considered. The existing code can be easily extended to include interactions of the first and second order.

Since the design of experiments technique performs design evaluations at discrete levels defined by the user a ***near-optimal*** solution is obtained. For a ***global-optimal*** solution, the user is advised to use any of the standard classical optimization tools available in the market. The architecture of IMCMA is well suited for easily integrating other software tools into IMCMA.

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Appendix A

The formulas for evaluation of variation in the performance parameter due to different values of modeling simplifications (*%var*) and the modified signal to noise (S/N) ratio used for identification of robust designs are presented in this appendix.

Let ${}^{ve}y_i$ represent the performance parameter values corresponding to the i^{th} virtual experiment (i.e. simulation) and *ve* (e.g.. *a*, *b*, *c*, *d* in Table 10) represent the repetitions of the virtual experiment for different combinations of modeling simplification parameters represented by the outer array. The percent variance in the performance parameter values due to the change in levels of each modeling parameter (*%var*) is computed as follows.

$$\%var = \frac{\left| \left(\sum_{i=1}^{N_i} {}^{ve}y_i \right)_{level1} - \left(\sum_{i=1}^{N_i} {}^{ve}y_i \right)_{level2} \right|}{N_i \bar{y}} \times 100 \qquad [1]$$

where,

$$\bar{y} = \left[\left(\sum_{i=1}^{N_i} \sum_{k=1}^{N_o} {}^{k}y_i \right) / (N_i No) \right] \qquad [2]$$

$\bar{y}$ = mean of all performance parameter values
N_i = number of experiments in the inner array
N_o = number of experiments in the outer array

For the parametric design presented in this report (as shown in Table 10), the modeling simplification parameters are XY-adjust (xy) and Z-adjust (z) with ni = 27 and no = 4. Thus,

$$\begin{aligned} \%var(xy) &= \frac{\left| \left(\sum_{i=1}^{27} {}^{a}y_i + \sum_{i=1}^{27} {}^{c}y_i \right) - \left(\sum_{i=1}^{27} {}^{b}y_i + \sum_{i=1}^{27} {}^{d}y_i \right) \right|}{27 \bar{y}} \times 100 \\ &= 0.31 \end{aligned}$$

Similarly,

$$\%var(z) = \frac{\left|\left(\sum_{i=1}^{27} {}^{a}y_i + \sum_{i=1}^{27} {}^{d}y_i\right) - \left(\sum_{i=1}^{27} {}^{b}y_i + \sum_{i=1}^{27} {}^{c}y_i\right)\right|}{27\bar{y}} \times 100$$
$$= 0.20$$

<u>**Modified signal to noise ratio**</u>: The Taguchi signal to noise ratios have met with considerable criticism and have been found to confound the mean and the variation effects in the performance parameter [10]. In our observations we found that the Taguchi lower is better S/N ratio was successful in only identifying designs with lower mean performance parameter values irrespective of variations in them. Hence, in order to identify designs with lower mean as well as variation in performance parameter values, a modified signal to noise ratio was formulated. The modified signal to noise ratio that minimizes the mean and the variation in the performance parameter is given by:

$$MOD(S/N) = -10LOG\left[\left(\frac{\sqrt{\sum_{i=1}^{N_o}(y_i - {}^{ve}\bar{y}_i)^2}}{N_o}\right)\left(\frac{{}^{ve}\bar{y}_i}{Min\left[\left\{({}^{k}y_i)_{k=1}^{N_o}\right\}_{i=1}^{N_i}\right]}\right)\right] \qquad [3]$$

where the mean of the *ith* virtual experiment across modeling simplifications are given as:

$${}^{ve}\bar{y}_i = \sum_{k=1}^{N_o} {}^{k}y_i \qquad [4]$$

In Eq. [3], $\left(\frac{\sqrt{\sum_{i=1}^{N_o}(y_i - {}^{ve}\bar{y}_i)^2}}{N_o}\right)$ quantifies the variation in performance parameter for different values of the parameters in outer array while $\left(\frac{{}^{ve}\bar{y}_i}{Min\left[\left\{({}^{k}y_i)_{k=1}^{N_o}\right\}_{i=1}^{N_i}\right]}\right)$ is a penalty factor that penalizes a design based on its mean performance parameter value. The penalty factor is a ratio of the mean performance parameter for a design and the minimum performance parameter value in

the complete set of virtual experiments performed. In this manner the MOD(S/N) ratio could be used to identify designs that have a low mean performance parameter value as well as a low variation in the performance parameter value across the outer array.

The Taguchi lower is better S/N ratio is given by

$$TAG(S/N) = -10LOG\left(\sum_{i=1}^{N_o} \frac{y_i^2}{N_o}\right) \qquad [5]$$

From the above expression it is clear that by using this S/N ratio the design with the lowest mean performance parameter value will be selected, irrespective of the variance in this value across the outer array. The above argument is clearly demonstrated in the example presented in Table 7. The table shows the performance parameter values for a virtual experiment set consisting of an L8 inner array and an L4 outer array. Using the Taguchi lower is better S/N ratio the design corresponding to virtual experiment 8 would be chosen as the robust design as it has the maximum S/N value of -37.52 dB, while, by using the modified S/N ratio MOD(S/N), the design corresponding to virtual experiment 7, which has the maximum S/N ratio value (-0.24 dB) would be chosen as the robust design. The design chosen by the Taguchi S/N ratio has the minimum mean temperature 74.99 °F (which was expected) and a variance of 126.02. The design chosen by using the modified S/N ratio has a mean temperature of 76.24°F which is slightly higher than the former but has a very low variance of 19.40. Thus using the modified S/N ratio a robust design having both low mean and low variance in performance was obtained. Using the modified S/N ratio, it is not necessary that designs with the lowest mean or lowest variance will be selected.

Table 10: EXAMPLE COMPARING TAGUCHI S/N AND MODIFIED S/N RATIOS

Orthogonal Inner Array: L8
Orthogonal Outer Array: L4

		L4 Outer Array							
		Performance Parameter ----							
	VE	a	b	c	d	Taguchi(S/N)	Avg	Variance	Mod(S/N)
L 8	1	77.05	92.08	78.17	70.50	-38.04	79.45	247.02	-5.95
	2	74.32	89.62	65.81	91.08	-38.16	80.21	448.75	-7.29
I A	3	72.47	83.08	73.26	95.14	-38.22	80.99	336.82	-6.70
n r	4	82.27	80.55	88.44	73.42	-38.21	81.17	114.49	-4.37
n r	5	88.35	80.24	88.54	61.17	-38.10	79.58	496.50	-7.47
e a	6	85.63	88.05	91.02	89.32	-38.94	88.51	15.49	-0.40
r y	7	75.38	74.10	79.93	75.56	-37.65	76.24	19.40	**-0.24**
	8	74.38	67.10	82.93	75.56	**-37.52**	74.99	126.02	-4.24
					MIN	-38.94	74.99	15.49	-7.47
					MAX	-37.52	88.51	496.50	-0.24

Appendix B

The following are a list of files and functions that comprise the ***DOVE*** module with brief descriptions of each of them.

1. *oas.lisp*: contains 8 orthogonal array instances, 5 of which are of level 2 and 3 of level 3.
2. *dove-run-imcma.lisp*: contains functions to run the physical idealization and finite element modeling and analysis KSs.
3. *define-design-space.lisp*: contains all the ***DOVE*** GUI functions to bring up the menus and take input from the USER.
4. *design-of-VEs.lisp*: this file contains all the functions to perform various ***DOVE*** tasks. Some of the important functions are described below.

   a) *dove-control-shell-function*: controls the looping of the entire FEMA process

   b) *ds-oa-map-function*: maps an appropriate orthogonal array that closely fits the user specified design space

   c) *dv-component-update-function*: updates the appropriate slot value for the corresponding component for the current design variable

   d) *pp-update-function*: updates the performance parameter value of the current virtual experiment inside the chosen orthogonal array

   e) *stat-analysis-function*: performs the statistical analysis of the experiments and predicts the optimum design configuration based on the mean levels of each design variable

   f) *write-out-dove-results*: writes out the user specified design space and the results of the statistical analysis

g) *read-dove-results*: reads the ***DOVE*** results onto a blackboard from an existing ".dove" file

All the above functions can easily be modified to work as knowledge sources (KSs). Since, currently the execution of various steps of the ***DOVE*** methodology are clearly sequential in nature, there is no real necessity for the above functions to perform as KSs.

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